Mountain Permafrost Distribution Modeling – A Geomorphometry-Remote Sensing Approach for the Hohe Tauern National Park, Austria

SIMON KÖNIG[1], JOHANNES A. SCHULTZ[1,2] , ANNA SCHOCH[1], JAN BLÖTHE[1], LOTHAR SCHROTT[1] & FRANK THONFELD[1,3]

Abstract: Mountain permafrost is an important geomorphological component of alpine environments with many influences and high spatial heterogeneity, having a considerable hydrological and hazard-related relevance. Hence, modeling of its distribution is an important task, especially in the densely populated Alps where a large share of infrastructure is located in or below permafrost-prone areas. We present a modeling approach solely relying on remotely sensed data. Permafrost distribution is modeled for the Hohe Tauern National Park, Austria, using airborne laser altimetry, Sentinel-2 data and a published rock glacier inventory. Modeling is performed with two techniques: logistic regression and random forest regression, with 13 geomorphic and spectral parameters derived from the input data. Our results show that random forest regression is more capable of predicting the correct permafrost probability of rock glaciers, whereas logistic regression is more in accordance with a previous distribution model for the same area. Both methods produce promising results that may further be expanded, improved and applied in new areas, for which additional validation would be feasible.

1 Introduction

Permafrost can be defined as ground remaining at or below 0°C for at least two consecutive years (GRUBER & HAEBERLI 2009). In contrast to high-latitude permafrost, the existence and properties of alpine permafrost are essentially a result of high mountain topography. Alpine permafrost is therefore a highly complex phenomenon, influenced by a variety of environmental variables. These can roughly be subdivided into three categories: first, macroclimatic conditions such as latitude and large-scale wind patterns modified by complex mountain topography, determine overall energy and moisture input. Second, topoclimatic conditions, predominantly elevation, aspect and slope, locally modulate temperatures and energy input from solar radiation. Third, local ground properties, e.g. lithology, grain size and hydrological properties again alter topoclimatic conditions. Some environmental variables like snow cover properties are a feature of all three categories; and in general, influences interact with each other, resulting in a complex framework of variables. Ultimately, this leads to large ground temperature differences over short distances of up to 15°C over 1 km and results in a very heterogenous spatial permafrost distribution in mountain areas (GRUBER & HAEBERLI 2009).

[1] Geographisches Institut Universität Bonn, Meckenheimer Allee 166, D-53115 Bonn,
E-Mail: simonkoenig@uni-bonn.de
[2] Ruhr-Universität Bochum, Geographisches Institut, Universitätsstraße 150, D-44801 Bochum
[3] Zentrum für Fernerkundung der Landoberfläche, Universität Bonn, Genscherallee 3, D-53113 Bonn

Climate change is more pronounced in high mountains, inducing increased temperatures that result in permafrost degradation (RANGWALA & MILLER 2012; HARRIS et al. 2009). While mountain permafrost is associated with several hazards, the destabilization of steep rock walls is especially important in this context: the presence of permafrost stabilizes these in numerous ways, and its degradation can result in increased frequencies of mass movements of different magnitudes, as witnessed by increased rockfall activity in the Alps during the hot summer of 2003 (GRUBER & HAEBERLI 2007; GRUBER et al. 2004). Large scale slope failure related to permafrost degradation can have severe consequences: in 2002, a permafrost-containing rock wall above the *Kolka* glacier in the Greater Caucasus collapsed, fell on the glacier and induced a complex landslide with a volume of 10^7 m^3, causing more than 100 fatalities (HUGGEL et al. 2005). A similar event is reported for the Swiss Alps as well (PHILLIPS et al. 2017).
Hence, and because permafrost as a solely thermal phenomenon is not directly visible (GRUBER & HAEBERLI 2009), spatial distribution modeling remains a key challenge in the young field of mountain permafrost research. Since the 1970s, various approaches have been developed, from basic evidence-based broad rules to complex energy flux models. HAEBERLI published the very first approach in 1975, creating evidence-based altitudinal thresholds for possible and probable permafrost existence in a small area in Switzerland. The first GIS-based model was developed in the early 1990s (KELLER 1992). In recent years, spatial resolution and precision of remotely sensed data have increased, and higher computational power as well as advancements in the field of permafrost research allow for improved model capabilities (HAEBERLI et al. 2010). GRUBER developed a first global estimation based on climate and elevation data with a resolution of ~1 km in 2012. DELUIGI et al. (2017) used different machine learning techniques to model permafrost distribution based on in-situ permafrost evidence. In this context, this study aims to develop a new approach to model permafrost distribution in the *Hohe Tauern National Park*, Austria. Its purpose is to model the local probability of permafrost occurrence using a relatively simple, empirical-statistical approach that solely relies on the analysis of remotely sensed data and does not require any field data for model calibration.

2 Study Area, Data and Methods

The *Hohe Tauern National Park* and its surroundings in the Austrian states of Carinthia, Salzburg and Tyrol was chosen as the study area (Fig. 1). The area accompanies the country's highest mountains and extends up to 3798 m above sea level. Permafrost distribution inside the area has been investigated by SCHROTT et al. (2012) based on extensive field surveys. The authors found that large parts of the park are likely to be underlain by permafrost, making the area most suitable for testing a different approach. The hazardous potential of mountain permafrost calls for the development of precise permafrost distribution assessments and continuous monitoring, as major infrastructure is located at high altitudes, including roads, reservoirs and touristic facilities like cable cars and skiing areas (SCHROTT et al. 2012).

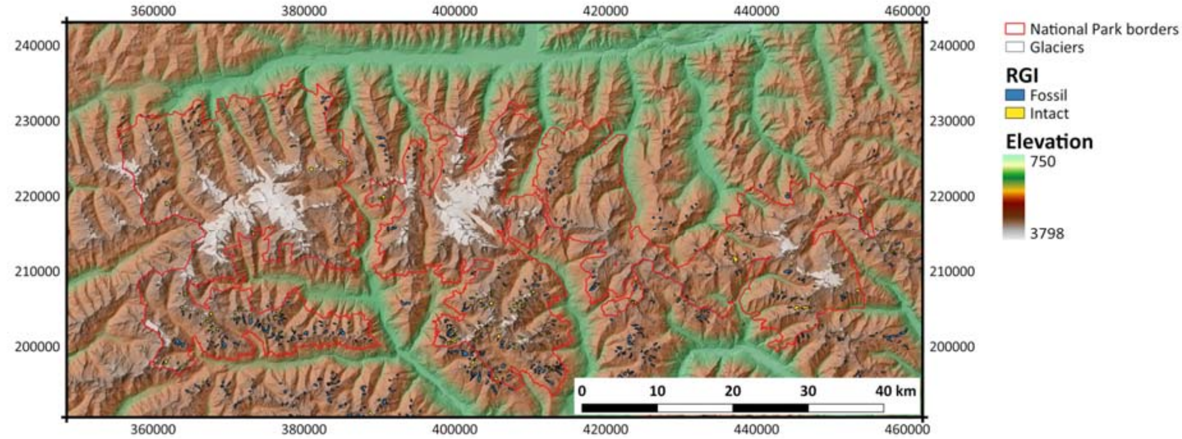

Fig. 1: Study area map, including elevation, rock glaciers and their activity status, glaciers and borders of the Hohe Tauern National Park. Projection: *MGI GK Austria West*

While heavily glaciated, the region also accommodates more than 800 rock glaciers, i.e. ice-containing forms of debris that creep downslope under the force of gravity, due to deformation of ice and water-saturated material at their base as well as deformation of their active layer, i.e. the surficial permafrost layers that thaw during summer (HAEBERLI et al. 2006), following freeze-thaw cycles. Intact rock glaciers are commonly viewed as indicators for permafrost presence, whereas relict rock glaciers that do not longer contain ice, be it through climatic changes or a rock glacier extending below the local altitudinal permafrost limit, indicate permafrost absence. This evidence of permafrost abundance makes the study area suitable to test the capabilities of permafrost models (KELLERER-PIRKLBAUER et al. 2012; HAEBERLI et al. 2006).

Three data sets provided input for the model: We merged seven digital elevation models (DEMs) of the bordering districts and states to extract information on topographic parameters. Data was gathered via airborne laser scanning with a resolution of 10 m and provided by the local authorities. To acquire information on how snow cover and vegetation develop throughout the year, a total of eight Sentinel-2 scenes were acquired, four for the Western and four for the Eastern part of the study area. For both parts, two scenes represented the beginning and end of growing season, two additional embodied start and finish of snow season, respectively. The scenes were chosen to match the respective dates as closely possible while also exhibiting a cloud cover as low as possible. Sentinel-2 has a resolution of 10 m in all bands relevant for this model, which matches the DEMs. Data was provided at Level 1c processing stage, i.e. radiometrically corrected and geolocated (ESA 2015). Finally, ground truth of permafrost presence and absence were derived from an inventory of rock glaciers for the Eastern Alps (KELLERER-PIRKLBAUER et al. 2012). The inventory consists of polygons of any known rock glacier that were derived by manually analyzing DEM derivatives. No direct field data was included to create these polygons.

The complete model procedure is documented in Fig. 2. Prior to distribution modeling itself, a variety of pre-processing steps were performed. The DEMs were provided as seven individual files with different properties; they had to be reprojected and merged into one large data set. Local errors and gaps along the district borders that arose during this process were corrected manually by interpolation from neighboring cells. In order to achieve a consistent spectral database, the

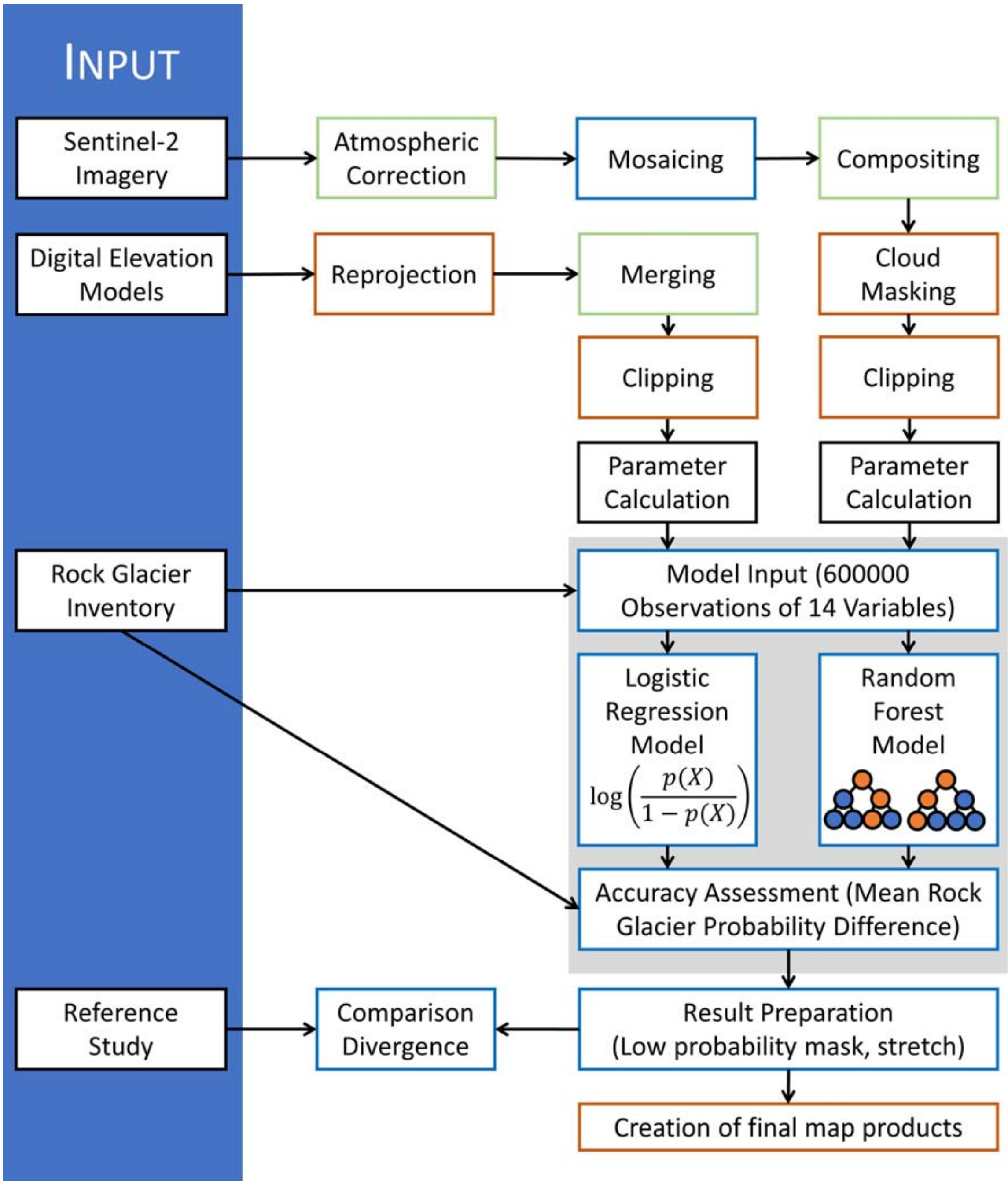

Fig. 2: Flowchart of the conducted procedure. Colors represent used software: R (blue), ArcGIS/QGIS (orange), SNAP/Sen2Cor (green). Black boxes indicate multiple software. The model itself is indicated by the grey box.

Level 1c Sentinel-2 imagery was atmospherically corrected and thereby converted to Level 2a processing level. This was achieved using ESA's *Sen2Cor* algorithm (ESA 2018). Since the popular *Fmask* cloud removal tool (ZHU et al. 2015) did not score satisfying results, clouds were masked out by manually using visual interpretation. Mosaics of the Eastern/Western images were created for all four dates. Finally, the merged DEM and Sentinel-2 mosaics were clipped to the study area extent. A total of 13 predictor variables were calculated from the inputs, serving as proxies for environmental conditions (Tab. 1). Activity status of rock glaciers was coded as a binary response variable – 0 for relict and 1 for intact specimens. Including this, the final data set consisted of 14 variables and amounted to nearly 1 Billion data points. Data was extracted for all rock glaciers. This smaller data set of 600,000 observations of the 14 variables, i.e. 8,4 Million data points, served as input for the model.

Tab. 1: Derived model predictors

Parameter	Relevance	Reference
Elevation (raw DEM values)	Air & surface temperatures	DELUIGI et al. (2017)
Aspect	Energy balance	ETZELMÜLLER et al. (2001)
Slope	Energy balance, hydrology, snow distribution	ETZELMÜLLER et al. (2001)
Plan & profile curvature	Hydrology, snow distribution	DELUIGI et al. (2017)
Topographic wetness index (TWI)	Hydrology	ETZELMÜLLER et al. (2001)
Local relief (defined here as z_{max}-z_{min})	Microclimate	ETZELMÜLLER et al. (2001)
Potential incoming solar radiation (PISR)	Energy balance	DELUIGI et al. (2017)
Wind shelter index (WSI)	Snow distribution	WINSTRAL et al. (2002)
Longitude & latitude	Climatic conditions	ARENSON & JAKOB (2010)
Maximum Normalized Difference Vegetation Index (NDVI) of all dates	Ground cover, active layer characteristics	DELUIGI et al. (2017)
Maximum Normalized Difference Snow Index (NDSI) of all dates	Snow cover characteristics & distribution	HALL et al. (2015)

To compare the results of a classical statistical and a machine-learning regression procedure, two model approaches were incorporated. Both are commonly used in a variety of scientific questions, including geomorphological topics and especially mountain permafrost research (BRENNING & TROMBOTTO 2006; DELUIGI et al. 2017). *Logistic regression* (LR), just as linear regression, is a parametric technique. It makes use of a logistic function to assign probabilities between 0 and 1:

$$\log\left(\frac{p(X)}{1-p(X)}\right) = \beta_0 + \beta_1 X_1 + \cdots + \beta_p X_p \tag{1}$$

where $p(X)$ is the probability to be estimated, $X_1, \dots, X_p$ are the predictors and $\beta_0, \dots, \beta_1$are the coefficients for these predictors that are fit using the maximum-likelihood approach (JAMES et al. 2017, 132-135):

$$\ell(\beta_0, \beta_1, \dots, \beta_p) = \prod_{i:y_i=1} p\,(x_i) \prod_{i':y_{i'}=0} \left(1 - p(x_{i'})\right). \tag{2}$$

Random forests (RF) is a machine-learning method introduced by BREIMAN (2001), feasible for both classification and regression. The method builds on the concepts of decision trees and bagging. A decision tree applies recursive binary splitting of predictor space, resulting in a tree-like structure. Bagging relies on creating a multitude of trees, each only incorporating a random sample of the training observations to decrease model variance and reduce possible overfitting. RF extends this idea by using a different random predictor subset in each tree, resulting in decorrelated trees. The final probabilities are assigned by averaging over the whole number of trees, which in this study amounted to 500 (JAMES et al. 2017).

LR and RF models were fit and applied to the complete study area individually, and their results validated in two ways: firstly, the mean modeled probabilities of any rock glacier were computed and compared for the assumed binary values. Secondly, a comparison to SCHROTT et al. (2012) was drawn: the authors' model output is expressed as an index between 1 and 100 for all likely permafrost occurrences, corresponding to all probabilities above 0.5 for this study's results. A difference between both was drawn for each pixel, normalized by the sum of both. For the creation of final maps, values below 0.5 were disregarded to only include areas with higher probabilities.

3 Results and Discussion

In general, both models produced similar results: permafrost probabilities greater than 0.5 are only abundant in the higher regions of the study area, surrounding the glacier covered peaks of the park's highest mountain groups (Fig. 3). A closer comparison reveals only subtle differences between both methods: LR predicts a more homogenous distribution with large areas of high probability in the inner and higher areas of the mountain groups, with sharply decreasing probabilities towards their margins, which appear to be 'fringy' (Fig. 3b). The total area of likely permafrost occurrence adds up to 13.5% of the study area. The permafrost bodies modeled by RF appear less homogenous and more differentiated. Permafrost areas are rather characterized by a slow and smooth increase in probability towards the highest peaks. In terms of area, RF models a slightly larger distribution: 14.8% is covered by permafrost. The similarity of both results is illustrated by their normalized difference as well: the mean for any pixel with an assigned probability greater than 0.5 amounts to just 0.016, i.e. on average, LR models a 1.6% higher probability.

Higher differences arise concerning the first validation method: RF is more capable of correctly predicting the binary values for rock glaciers. The mean difference between assumed and predicted value of all rock glaciers is 0.143 for LR and 0.017 for RF, while both methods perform better on relict rock glaciers (Fig. 4). The better performance of RF is also supported by qualitative assessment of the RF detail map, where intact rock glaciers are almost exclusively located inside high-probability areas and relict specimen are outside (Fig. 3c), a characteristic that is less detectable in the detailed LR map (Fig. 3b). The results produced by LR exhibit less deviance from the map by SCHROTT et al. (2012), with a difference that is 0.007 lower compared to RF. This however is fairly small compared to the overall deviances of both models, which amounts to 0.374 for RF and 0.367 for LR. I.e., distinctions in normalized difference to SCHROTT et al. (2012) are relatively high, with only slight differences between LR and RF.

Despite these differences in detail, model results are in general in accordance with the previous, field-based study by SCHROTT et al. (2012): permafrost is distributed over a relevant part of the national park's higher regions, and while both LR and RF show an increase of probability with rising altitude, results are not that simple and reflect more complex environmental variable relationships. In general, the results attained by our study are in good agreement with earlier findings

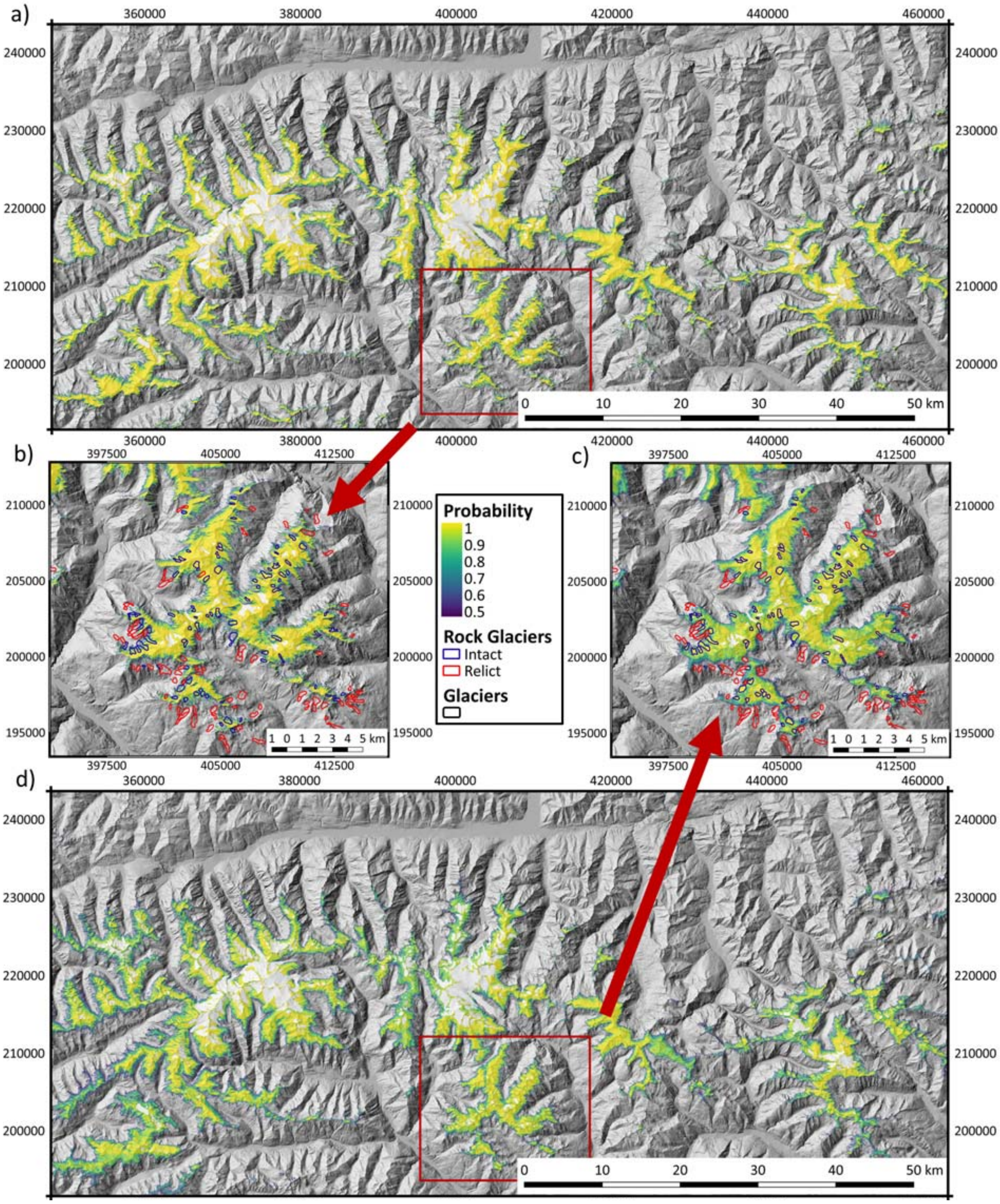

Fig. 3: Permafrost distribution maps. Logistic regression (a, b) models more homogenous permafrost bodies with higher probabilities than random forest regression (c, d). Projection: *MGI GK Austria West*

(SCHROTT et al. 2012) and demonstrate the potential of using both machine learning and probabilistic approaches in the prediction of alpine permafrost. The similar approach by DELUIGI et al. (2017) used machine learning techniques as well, the authors calibrated their models with field data, however. Yet, both approaches elucidate the abilities of machine learning for mountain permafrost distribution modeling and in addition shows that remotely sensed data is a sensible input for this task.

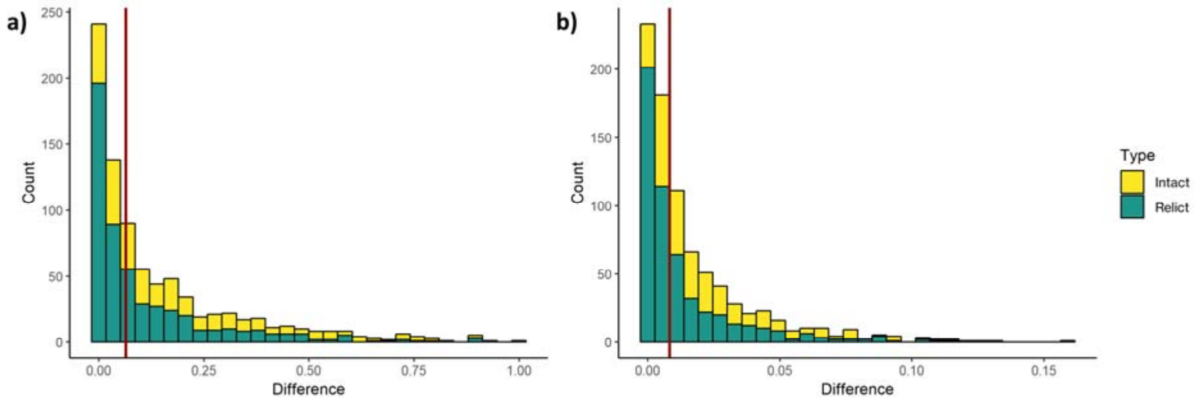

Fig. 4: Stacked histograms of the difference between mean modeled and the assumed binary values for any rock glacier. As the x scales depict, logistic regression (a) results in higher deviances, compared to random forest regression (b). Red lines represent mean values for both.

While its renouncement of field data is a distinct advantage of this study's approach in terms of rapid low cost, high resolution mapping of mountain permafrost distribution as well as high transferability to other study areas, it also results in the disadvantage that it lacks truly independent test data for validation. Using the values of rock glaciers that were previously used for training to estimate model errors may be insufficient, as only the training error is calculated. In addition, rock glaciers and their information on permafrost status may not necessarily be representative for whole study areas, as they represent only small parts of the region and tend to exhibit lower temperatures and hence higher permafrost occurrence probabilities than their surroundings (HAEBERLI et al. 2006). Moreover, rock glaciers are a prominent, but not always present feature of periglacial environments, making the transfer to other regions difficult. Comparison of different model outputs is feasible in general and the results by SCHROTT et al. (2012) provide a valuable source of information, but are yet a definite validation source, as their model is also based on assumptions and may exhibit errors. Finally, the chosen predictors cannot completely depict actual influences on permafrost distribution, though they represent a broad range of environmental variables on all scales of influence. Hence, before application to other regions, the model should be validated with independent data and sensitivity studies may be conducted to test which parameters present actual conditions to the highest grade.

4 Conclusion

The approach presented in this study results in high-resolution maps of mountain permafrost abundance probabilities that were created using only remotely sensed data. It is data-driven and does not rely on expert input, nor field measurements. The existence of a rock glacier inventory is an advantage in this context, as deriving these inventories from airborne LiDAR is possible, but remains an elaborate and time-consuming task (KELLERER-PIRKLBAUER et al. 2012). Consequently, future extensions of this approach could possibly incorporate automatic rock glacier detection to automatize the whole process and make it more data-driven (BRENNING 2009). A challenge in this context is the distinction between intact and relict rock glaciers that today still requires expert knowledge (KELLERER-PIRKLBAUER et al. 2012). Additionally, an inclusion of additional remote sensing products may improve the model: especially, time series analyses of snow cover and vegetation could provide better estimates of their development. The use of radar data to include more sophisticated snow cover proxies as well as thermal infrared data for derivation of land surface temperatures are promising ideas in this context as well.
The high accuracies of random forest regression illustrate the benefits of using machine learning methods for environmental modeling. Hence, it appears natural to also test other techniques in this context, such as support vector machines. Notably, the use of deep learning algorithms which have often been used for a multitude of questions and have proven to be highly accurate, may especially benefit this approach (ZHU et al. 2017). All suggested techniques could also be used in continuous spatiotemporal monitoring of permafrost conditions, e.g. in precaution to the hazards described in the introduction. Combined with a continuously improved understanding of mountain permafrost in its whole, modeling of its distribution can represent an actual benefit for local communities.

5 Acknowledgements

We thank Jan-Christoph Otto for providing us with the data as published in SCHROTT et al. (2012). The rock glacier inventory (KELLERER-PIRKLBAUER et al. 2012; LIEB et al. 2012) is freely available at *https://doi.pangaea.de/10.1594/PANGAEA.869805* under Creative Commons Attribution 3.0. Outlines of glaciers in Figs. 1 & 3 (FISCHER et al. 2015) are available under Creative Commons Attribution 3.0 at *https://doi.pangaea.de/10.1594/PANGAEA.844985*. The DEMs as well as the outline of the national park borders can be found at *http://data.gv.at* under Creative Commons Attribution 3.0.

6 References

ARENSON, L. & JAKOB, M., 2010: A New GIS based Mountain Permafrost Distribution Model. Proceedings of the 6th Canadian Permafrost Conference, 452-458.

BREIMAN, L., 2001: Random Forests. Machine Learning, **45**, 5-32.

BRENNING, A., 2009: Benchmarking classifiers to optimally integrate terrain analysis and multispectral remote sensing in automatic rock glacier detection. Remote Sensing of Environment, **113**, 239-247.

BRENNING, A. & TROMBOTTO, D., 2006: Logistic regression modeling of rock glacier and glacier distribution: Topographic and climatic controls in the semi-arid Andes. Geomorphology, **81**, 141-154.

DELUIGI, N., LAMBIEL, C. & KANEVSKI, M., 2017: Data-driven mapping of the potential mountain permafrost distribution. The Science of the total environment, **590-591**, 370-380.

ETZELMÜLLER, B., ØDEGÅRD, R. S., BERTHLING, I. & SOLLID, J. L., 2001: Terrain parameters and remote sensing data in the analysis of permafrost distribution and periglacial processes: principles and examples from southern Norway. Permafrost and Periglacial Processes, **12**, 79-92.

EUROPEAN SPACE AGENCY (ESA), 2015: Sentinel-2 User Handbook. https://sentinel.esa.int/documents/247904/685211/Sentinel-2_User_Handbook.

EUROPEAN SPACE AGENCY (ESA), 2018: Sen2Cor Configuration and User Manual. http://step.esa.int/thirdparties/sen2cor/2.5.5/docs/S2-PDGS-MPC-L2A-SUM-V2.5.5_V2.pdf.

FISCHER, A., SEISER, B., STOCKER-WALDHUBER, M. & ABERMANN, J., 2015: The Austrian Glacier Inventory GI 3, 2006, in ArcGIS (shapefile) format. https://doi.pangaea.de/10.1594/PANGAEA.844985.

GRUBER, S., 2012: Derivation and analysis of a high-resolution estimate of global permafrost zonation. The Cryosphere, **6**, 221-233.

GRUBER, S. & HAEBERLI, W., 2007: Permafrost in steep bedrock slopes and its temperature-related destabilization following climate change. Journal of Geophysical Research, **112**, 301.

GRUBER, S. & HAEBERLI, W., 2009: Mountain Permafrost. Permafrost Soils, R. Margesin (ed.), Springer Verlag, Berlin/Heidelberg, 33-44.

GRUBER, S., HOELZLE, M. & HAEBERLI, W., 2004: Permafrost thaw and destabilization of Alpine rock walls in the hot summer of 2003. Geophysical Research Letters, **31**, L13504.

HAEBERLI, W., 1975: Untersuchungen zur Verbreitung von Permafrost zwischen Flüelapass und Piz Grialetsch (Graubünden). Mitteilung der Versuchsanstalt für Wasserbau, Hydrologie und Glaziologie. Zürich.

HAEBERLI, W., HALLET, B., ARENSON, L., ELCONIN, R., HUMLUM, O., KÄÄB, A., KAUFMANN, V., LADANYI, B., MATSUOKA, N., SPRINGMAN, S. & MÜHLL, D. V., 2006: Permafrost creep and rock glacier dynamics. Permafrost and Periglacial Processes, **17**, 189-214.

HAEBERLI, W., NOETZLI, J., ARENSON, L., DELALOYE, R., GÄRTNER-ROER, I., GRUBER, S., ISAKSEN, K., KNEISEL, C., KRAUTBLATTER, M. & PHILLIPS, M., 2010: Mountain permafrost: development and challenges of a young research field. Journal of Glaciology, **56**, 1043-1058.

HALL, D. K., FREI, A. & DÉRY, S. J., 2015: Remote sensing of snow extent. Remote Sensing of the Cryosphere, M. Tedesco (ed.), Chichester, UK, 31-47.

HARRIS, C., ARENSON, L. U., CHRISTIANSEN, H. H., ETZELMÜLLER, B., FRAUENFELDER, R., GRUBER, S., HAEBERLI, W., HAUCK, C., HÖLZLE, M., HUMLUM, O., ISAKSEN, K., KÄÄB, A., KERN-LÜTSCHG, M. A., LEHNING, M., MATSUOKA, N., MURTON, J. B., NÖTZLI, J., PHILLIPS, M., ROSS, N., SEPPÄLÄ, M., SPRINGMAN, S. M. & VONDER MÜHLL, D., 2009: Permafrost and climate in Europe: Monitoring and modelling thermal, geomorphological and geotechnical responses. Earth-Science Reviews, **92**, 117-171.

HUGGEL, C., ZGRAGGEN-OSWALD, S., HAEBERLI, W., KÄÄB, A., POLKVOJ, A., GALUSHKIN, I. & EVANS, S. G., 2005: The 2002 rock/ice avalanche at Kolka/Karmadon, Russian Caucasus: assessment of extraordinary avalanche formation and mobility, and application of QuickBird satellite imagery. Natural Hazards and Earth System Science, **5**, 173-187.

JAMES, G., WITTEN, D., HASTIE, T. & TIBSHIRANI, R., 2017: An introduction to statistical learning. With applications in R. Springer texts in statistics. Springer Science + Business Media, New York, Heidelberg, Dordrecht, London.

KELLER, F., 1992: Automated mapping of mountain permafrost using the program PERMAKART within the geographical information system ARC/INFO. Permafrost and Periglacial Processes, **3**, 133-138.

KELLERER-PIRKLBAUER, A., LIEB, G. K. & KLEINFERCHNER, H., 2012: A new Rock Glacier Inventory of the Eastern European Alps. Austrian Journal of Earth Sciences, **105**, 78-93.

LIEB, G. K., KELLERER-PIRKLBAUER, A. & KLEINFERCHNER, H., 2012: Second rock glacier inventory (RGI2) of Central and Eastern Austria, link to Shapefile, supplement to: Kellerer-Pirklbauer, A., Lieb, G. K. & Kleinferchner, H., 2012: A new rock glacier inventory of the eastern European Alps. Austrian Journal of Earth Sciences, **105**(2), 78-93. https://doi.pangaea.de/10.1594/PANGAEA.869805.

PHILLIPS, M., WOLTER, A., LÜTHI, R., AMANN, F., KENNER, R. & BÜHLER, Y., 2017: Rock slope failure in a recently deglaciated permafrost rock wall at Piz Kesch (Eastern Swiss Alps), February 2014. Earth Surface Processes and Landforms, **42**, 426-438.

RANGWALA, I. & MILLER, J. R., 2012: Climate change in mountains: a review of elevation-dependent warming and its possible causes. Climatic Change, **114**, 527-547.

SCHROTT, L., OTTO, J.-C. & KELLER, F., 2012: Modelling Alpine Permafrost Distribution in the Hohe Tauern Region, Austria. Austrian Journal of Earth Sciences, **105**, 169-183.

WINSTRAL, A., ELDER, K. & DAVIS, R. E., 2002: Spatial snow modeling of wind-redistributed snow using terrain-based parameters. Journal of Hydrometeorology, **3**, 524-538.

ZHU, X. X., TUIA, D., MOU, L., XIA, G.-S., ZHANG, L., XU, F. & FRAUNDORFER, F., 2017: Deep Learning in Remote Sensing: A Comprehensive Review and List of Resources. IEEE Geoscience and Remote Sensing Magazine, **5**, 8-36.

ZHU, Z., WANG, S. & WOODCOCK, C. E., 2015: Improvement and expansion of the Fmask algorithm: cloud, cloud shadow, and snow detection for Landsats 4-7, 8, and Sentinel 2 images. Remote Sensing of Environment, **159**, 269-277.